Advanced Signal Processing Techniques for Fetal ECG Analysis

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Abstract

In response to the PhysioNet/CinC Challenge 2013: Noninvasive Fetal ECG [1] we developed an algorithm for fetal QRS (fQRS) positions estimation based on a set of classic filters, which enhances the fetal ECG, combined with a robust QRS detection technique based on Christov's beat detection algorithm. These steps provides necessary information for the maternal ECG (mECG) cancellation, which is based on the technique provided by the Challenge organizers. Our work extends the provided algorithm with mECG reduction quality check and in case of insufficient reduction the mECG reduction algorithm is applied again until the criteria for sufficient reduction based on energy around the maternal QRS complex are satisfied. After noise reduction two techniques for fQRS were applied - one provided by the organizers and second based on entropy estimation. Results from both detectors are then corrected creating another set of fQRS positions estimates and from all sets of fQRS estimates there is selected one with the smallest standard deviation of fetal R-R distances. Our method results are 249.784 for Event 1/4 and 21.989 for Event 2/5 respectively. We did not participate in Event 3 - QT interval estimation.

1. Introduction

This paper describes our solution to the PhysioNet/CinC Challenge 2013: Noninvasive Fetal ECG. Our algorithm for detection of fetal QRS complexes from the abdominal ECG is based on the method provided by organizers to all participants. Our aim is to improve fQRS detection rate in sense of two measures used as scoring function - Root Mean Square Error between our fHR and fRR estimates and referential estimates.

2. Data

The Challenge data have been divided into 3 groups - training, testing and validation. Training data were available to participants with all annotations. Training dataset contains 75 abdominal recordings. Testing data were available to participants without annotations and they contained 100 recordings. Validation dataset is a closed dataset, which is not freely available to participants.

3. Method

Our method is an extension of the method proposed by organizers. The algorithm is divided into several steps (Fig. 1).

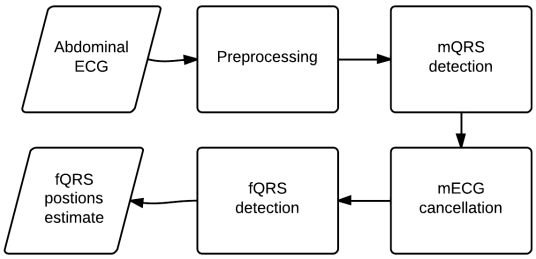

Figure 1. Process of fQRS detection. First is the abdominal ECG preprocessed then mQRS complexes are cancelled and finally fQRS are detected.

The very first step of the algorithm detects missing samples in data and replaces the missing values with approximate values estimated by Piecewise Cubic Hermite Interpolating Polynomial [2]. Next the isoline cancellation is done using median filer:

$$y[n] = median\{x[n+i], i = 0, ..., N-1\}, \quad (1)$$

where y represents filtered signal, x represents original signal and N is length of the filter. The procedure for isoline suppression follows:

- Decimate ECG signal with decimation factor 20.
- Filter resulting signal with median filter of length 10.
- Interpolate filtered signal into original length with low-pass interpolation. Interpolated signal represents base line wander.
- Subtract interpolated signal from original ECG.

The result is then passed to 50 point moving averaging FIR filter. Resulting averaged signal is then subtracted from the result of isoline filtering. The subtraction result is successively used for the detection of mQRS complexes.

For detection of mQRS we used Christov's QRS detection algorithm described in [3]. the algorithm is based on transforming ECG signal into signal complex lead using complex lead transform defined as:

$$X[n] = \frac{1}{L}\sum_{j=1}^{L}|x_j(n+1) - x_j(n-1)|, \qquad (2)$$

where $X[n]$ is nth sample of signal calculated by complex lead transform, L is number of measured ECG leads, $x_j(n)$ is nth sample from jth lead. Then the combined adaptive threshold $\mathbf{MFR}$ is employed for detection of QRS complexes. Adaptive threshold combines three thresholds:

- Threshold $\mathbf{M}$ (adaptive steep-slope threshold) - reflects the amplitude of currently detected beats.
- Threshold $\mathbf{F}$ (adaptive integrating threshold) - reflects the presence of high frequency noise in data and increases the combined threshold in that case.
- Threshold $\mathbf{R}$ (adaptive beat expectation threshold) - is intended to deal with heartbeats of normal amplitude followed by beats with very small amplitude.

In our case selected two abdominal ECG channels have been used for the mQRS detection. Selection is done using kurtosis criterion - channels with the highest kurtosis were selected for detection of mQRS. The kurtosis criterion was used because of observation that ECG has super-Gaussian distribution [4].

After detection of mQRS the mECG cancellation algorithm was applied. This algorithm is an enhanced version of the method provided by the Challenge organizers. The whole process of mECG cancellation is depicted on Figure 2. The algorithm works with windows of 20 mQRS and processes each window separately during the creation of mECG estimate. First mQRS template is created using averaging of mQRS complexes within the window. Then the mECG estimate in 20 mQRS window is created using the template and positions of detected mQRS. After the process of construction the estimated mECG is subtracted from abdominal ECG and decision about cancellation quality is taken. Decision algorithm checks whether the average energy around positions of mQRS is sufficiently small (average energy per beat of 700 samples length is less than 10 μV^2) and if not mECG cancellation algorithm starts again. This leads to better mECG suppression in presence of noise.

Final step of our method contains detection of fQRS complexes on preprocessed abdominal ECG signals with two detectors: Sameni's detector (provided by challenge organizers [1]) and entropy based detector. Sameni's detector has been provided from the Challenge organizers and it searches maxima within window of predefined length. Our detector estimates non-normalized Wavelet Shanon's entropy of 5 consecutive samples. Non-

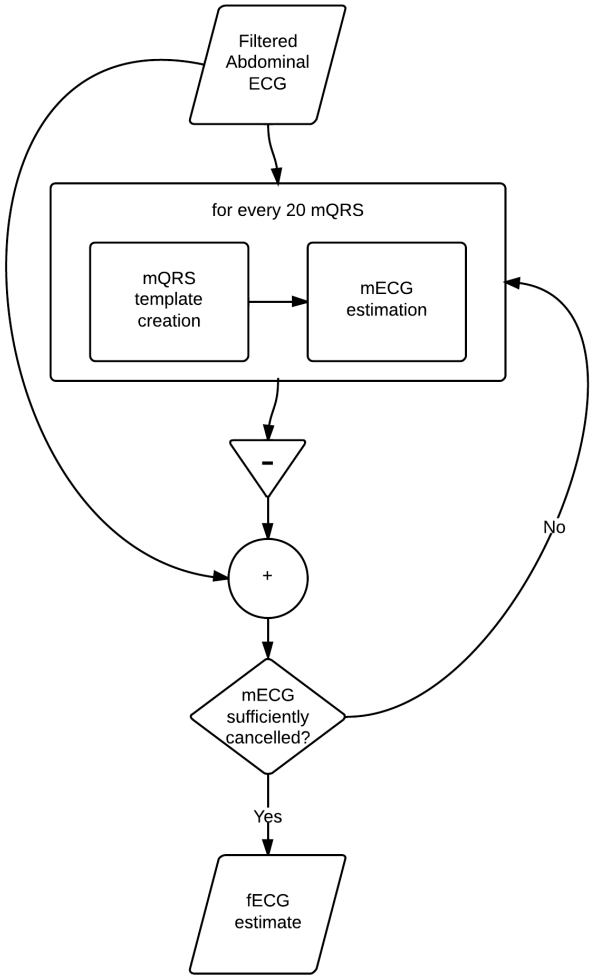

Figure 2. mQRS cancellation procedure.

normalized WaveletShanon's entropy [5] is defined as:

$$E(s) = -\sum_{i} s_i^2 ln s_i^2, \qquad (3)$$

where s_i are the signal samples and $E(s)$ is the entropy of given signal. In our detection algorithm wavelet entropy $E(s)$ of 5 consecutive signal samples is computed. This leads to a transformed signal with enhanced fQRS positions. Using absolute value of the transformed signal we search for the peaks within applying following criteria:

- Peak height is at least 200.
- Peak distance is at least 300 ms from the previous one.

After both detectors return their estimates of fQRS on all abdominal recordings all estimates are passed to a correction algorithm, which checks fQRS positions and tries to estimate missing QRS complexes. Detection of missing QRS complexes is based on detection of outlier values in fetal tachogram created from the estimated fQRS. Outlier value in tachogram is detected, when current fetal RR

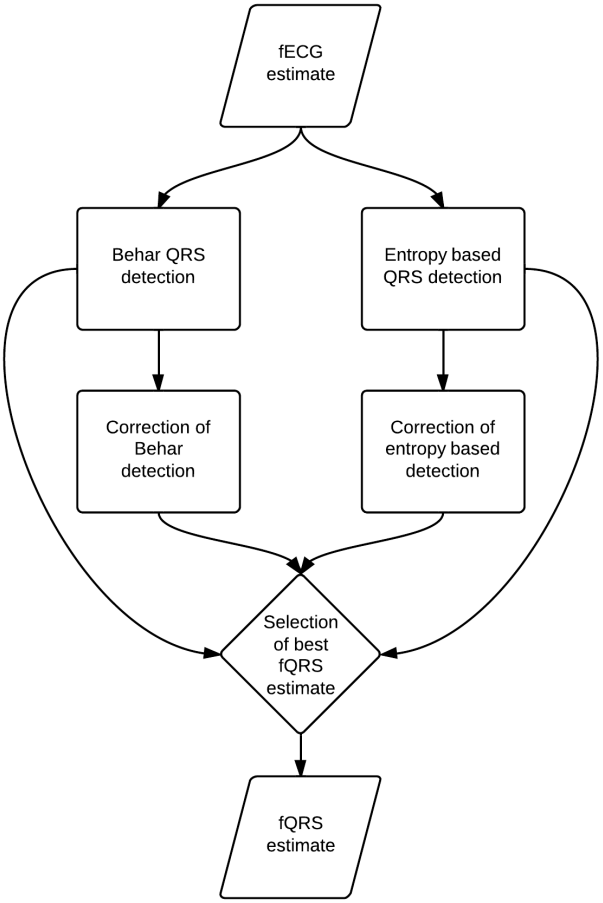

Figure 3. fQRS detection and selection procedure.

Table 1. Results

Entry	Training set	Challenge results
Entry 1	549/37.5	701.2/42.2
Entry 6	126/19.7	306.3/24
Entry 7	113/16.1	352.1/20.7
Entry 8	95.5/17.5	249.8/22
Entry 9	94.9/17.3	255/21.8
Entry 11	65.1/16.7	288.4/22

value is greater than 110% of previous and following fetal RR mean value. This detects the outlier peaks in fQRS estimates and points out the problematic detection regions. Then the correction tries to find correct position of fQRS. Search procedure is divided into 3 cases:

- Previous fQRS is closer or farther than 20% of mean fetal RR - this means that we need to search new position of previous fQRS from current fQRS in window of ± 100 samples around current fQRS position - mean fetal RR. New fQRS position is found as maxima within the window.
- Following fQRS is closer or farther than 20% of mean fetal RR - this means that we need to search new position of following fQRS from current fQRS in window of ± 100 samples around current fQRS position + mean fetal RR. New fQRS position is found as maxima within the window.
- Both previous and following fQRS are closer or farther than 20% of mean fetal RR - this means that we need to search for new position of current fQRS. Search is done in ± 100 samples window around position of middle between previous and following fQRS. New fQRS position is found as maxima within the window

From estimated fQRS positions and their corrections decision algorithm chooses one with minimal standard deviation of R-R distances. This is then declared to be the best solution of fQRS detection. The process of fQRS detection is shown on Figure 3.

4. Results

The Challenge is scored using two scores (QT interval score is omitted because we are not participating in the event):

- Event 1/4 - Fetal heart rate measurement: Scores are computed from the differences between matching reference and test FHR measurements. The score is computed as mean square error between matching sequences.
- Event 2/5 - Fetal RR interval measurement: Scores in these events are computed from the differences between matching reference and test RR intervals. The score is computed as mean square error between matching sequences.

Our results are presented in Table 1. First score is score for Event 4 and second score (after backslash) for Event 5. We show scores for both training and testing data (results for Events 1 and 2 were not available before submission of our paper). Our scores have improved during the evolution of our algorithm on training data. On testing data we can observe that our algorithm have slower improvement and get worse in entry 11.

5. Discussion

We developed a solution for the Physionet/CinC 2013 Challenge: Noninvasive Fetal ECG, which is based on solution provided by the Challenge organizers. During the development we improved gradually: preprocessing, mECG cancellation and fQRS estimation steps. We are trying to keep the solution as simple as possible in order to keep its usability in further deployment. During evaluation of our results we discovered an error in scoring function provided by the Challenge organizers, which has lead after the correction to worse results than we achieved previously (underestimated error). This problem emerged with our Entry 8 submission and thus we had short time to react on changes of the scoring function. Nevertheless we

developed an algorithm, which is strong in estimation of fetal RR time series.

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